Utilizing Economic Activity and Data Science to Predict and Mediate Global Conflict

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Abstract

The year 2020 has left many individuals finding that their lives are continually being changed based on the state of global circumstances. Some believe that these changes have given many citizens the opportunity to understand the interconnected nature of global actions and domestic consequences.

Our preliminary hypothesis and research centers around the belief that an informed global population produces a safer, and better prepared, global society. It is our understanding that when individuals are able to reasonably prepare or expect conflict, early mediation and resource management can not only save tremendous funds, but also save numerous lives.

We believe that creating a source of accessible predictive models is not only possible, but can be done without tremendous resource demand by tracking key pointers within the global economy and historic conflict triggers.

Key Concepts

Conflict Prediction, Data Science, Global Investment and Trade

Introduction

Were there economic pointers attached to Covid-19? Could taking a step back from relying on a country's hearsay when it comes to solving and containing natural, civil, or international disasters have allowed more lives to be saved, more hospitals to be prepped, and more civilians to be informed?

Living through a global pandemic in a divided world that is routinely being flooded with misinformation, one begins to wonder if the tools needed to mediate global and local catastrophes are available. From this, the question very quickly becomes not only whether there are predictive tools, but whether they are readily available for citizens as well as countries.

Are there factors global citizens can look further into that may correlate with, and hopefully predict, conflict? And if they are available, how can we utilize Data Science, Machine Learning and Artificial Intelligence to aid in keeping global societies honest?

In pursuit of the answer to these very dire questions, the goal became truly clear: creating a system or method of taking in public data and simplifying its points into concise conflict predictions. The task of understanding what causes conflict soon followed.

It should be stated and understood that there are an infinite number of possible triggers to conflict. Acknowledging this, it also is clear that our small team, nor any team, could ever account for every aspect, so we needed to zoom out and get a bigger picture before we could narrow down our options. The main field acknowledged measurable factors are climate change, large scale human migration, education, new technologies, economic motive, regional motive, political motive, and social factors [1][2]. Each of these dimensions has a sure effect on human action, but measuring and accounting for each seemed still too large. So, we looked at what others in the field had done.

Related Work

We are certainly not the first to try and take on the challenge of predicting and simplifying human aggressions into a system that global citizens could access in order to prepare and hold each other accountable. Two significant preexisting systems are ViEWS [3], created by Uppsala University for the Department of Peace and Conflict Research located in Sweden, and GUARD [4], created by the United Kingdom's Alan Turing Institute for its Defense and Security programs.

Both are impressive programs, they highlight areas of likely conflict, and seem to take in different dimensions of data. However, they also seem to be focused solely on a specific area of conflict (instead of the entire world and its territories) and the data they were taking in required a large amount of human input. It seems that without gross amounts of human resource and input, the output data would not be easily obtainable by any global citizen.

Moving Towards Efficiency

Our team took advantage of our position as a small but passionate group and realized that our size meant zero stakes in the matter of producing accurate predictions. We are not funded or relaying details to larger organizations that rely on accurate data – at least not yet. Quickly we realized that because of this, we can experiment wildly with new concepts that in theory could prove to be effective, if not leaping steps in the right direction.

Could there be merit to studying one portion of the contributors of conflict?

To further this revelation of the freedom by our project size, we started digging deeper into something that we could have access to all the time, the economy. What if we took public and government trading, stock, and hoarding into account and found small changes in investment that tip whether a country or its citizens are preparing for some sort of conflict that the rest of the world isn't privy to yet?

Thought Process

Our thought process is as follows:

Imagine you are the leader of a country, and you have just realized that there is a virus within your borders that has hazardous trends likely to cause a global pandemic if it were to remain unchecked.

Thinking as a strong leader, you want to make sure that your own country has the supplies and necessities in order to survive the potential wave of pandemic to follow. To do this, you now invest heavily in Personal Protective Equipment (PPE), hoard food and take investments from the transportation industry and move them into your own domestic no-contact shipping.

In the name of self-preservation and protection from the chaos to follow, ideally this would all happen before you tipped off, and likely downplayed, the severity of the situation to the rest of the international community.

The flip side:

Now, take this scenario and imagine that there was a widely available and easily readable system that could point to potential areas of conflict or unrest by observing economic activity that historically was paired with international and/or domestic conflict. It lets the entire world know that you, the strong leader, and your country are acting and investing in a way that would point to domestic issues.

In this new scenario, as a response to this system there would be widespread accountability, resource management, crisis mitigation, global security and knowledge accessibility potentially saving thousands, if not millions, of lives.

Real Application

Some version of this scenario has turned into reality within the past 12 months. The unfortunate reality is that the real time consequence has been the unnecessary loss of life.

With history and this modern reality comes the added value in the potential to track the economy in a way that pairs slight changes with historical conflict to prevent human and economic loss.

First Approach

To begin with, our team hoped to use an existing tool that would enable more ability on our end to make conflict predictions.

To create this system, we started by experimenting with the Amazon Web Services (AWS) product Amazon Forecast. AWS is a cloud platform that offers various products in machine learning, game technology, security and the like. Forecast is well known for its time-series forecasting and is popular with companies that hope to predict supply chain demand and business metrics [5].

We believed that the tool's ability to easily account for irregularities such as holidays and adapt to the nature of the data sets, made it an appealing product given its forgiving nature.

After reformatting the product placement data sheet to Forecast standards, we started off by testing the product on soybean imports. We quickly encountered many walls that were preventing us from being as effective as possible.

The product was unable to accommodate multiple data sets with varying time series. We realized that Forecast easily accommodates more stagnant datasets, such as metadata, to be included. We ultimately need one that can support many time series data sets. Thus, we abandoned Amazon Forecast and decided it would be best to continue with a model of our own that we could tailor to our own research.

Current Approach

Figure 1: US Exports of Corn to Saudi Arabia

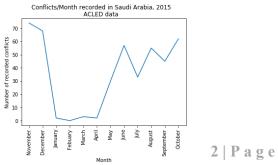


Figure 2: Conflicts per month in Saudi Arabia

US exports of soy to Indonesia, 2015 ERS summary of data released by Census Bureau, U.S. Department of Commerce, through December 7, 2016

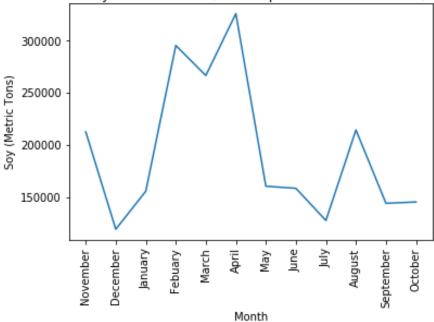


Figure 3: US Exports of Soy to Indonesia

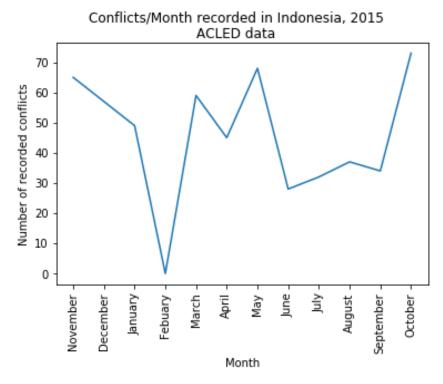


Figure 4: Conflicts per month in Indonesia

	Region	Nov. 2015	Dec. 2015	Jan. 2015	Feb. 2015	Mar. 2015	Apr. 2015	May 2015	Jun. 2015	Jul. 2015	Aug. 2015	Sep. 2015	Oct. 2015
0	Japan	418341	342761	560135	656818	1063283	972244	1248961	1249743	1440594	1218643	1643916	385733
1	Mexico	753709	1029277	890251	1098896	1249991	1372285	1344127	1227860	1114138	1216459	1251920	1001596
2	Colombia	176314	474488	374044	530066	460149	1084779	132383	10708	246717	282138	345006	429814
3	Taiwan	58624	65845	29829	60114	92629	387312	162273	379944	303823	386162	311092	57308
4	Peru	121806	237184	228035	154869	232496	260310	189307	256474	132569	340905	286504	187155
5	Saudi Arabia	0	143703	153497	0	190963	225	199586	360281	197624	142763	133777	139930
6	Guatemala	73875	30040	48835	116842	70746	85080	77979	83112	73127	95095	85592	79187

Table 1: Sample USDA Export data from November 2015 to October 2015. Showing quantity of product moved from each country.

	data_id	iso	event_id_cnty	event_id_no_cnty	event_date	year	time_precision	event_type	sub_event_type	actor1	 location
3	6439513	682	SAU5708	5708	31 December 2015	2015	1	Explosions/Remote violence	Shelling/artillery/missile attack	Military Forces of Yemen (2015-2016) Supreme R	 Jizan
84	1 7084802	682	SAU5701	5701	30 December 2015	2015	1	Explosions/Remote violence	Shelling/artillery/missile attack	Military Forces of Yemen (2015-2016) Supreme R	 Abha Regional Airport
140	6 6439519	682	SAU5706	5706	30 December 2015	2015	1	Explosions/Remote violence	Shelling/artillery/missile attack	Military Forces of Yemen (2015-2016) Supreme R	 Jizan
14	7 6439520	682	SAU5707	5707	30 December 2015	2015	1	Explosions/Remote violence	Shelling/artillery/missile attack	Military Forces of Yemen (2015-2016) Supreme R	 Wadi Aleeb
170	6439548	682	SAU5704	5704	30 December 2015	2015	1	Battles	Armed clash	Military Forces of Yemen (2015-2016) Supreme R	 Al Khobh
2732	3 6446985	682	SAU5065	5065	29 March 2015	2015	1	Battles	Armed clash	Unidentified Armed Group (Saudi Arabia)	 Riyadh :
2848	3 6447214	682	SAU5064	5064	16 March 2015	2015	1	Violence against civilians	Attack	Unidentified Armed Group (Saudi Arabia)	 Medina :

Table 2: Sample Armed Conflict Location & Event Data Project (ACED) data for conflict showing December and March dates with varying types of conflict (shelling/artillery/missile attack, armed clash, attack etc)

The first two figures, figures 1 and 2, provide an example of the preliminary correlation between economic activity and conflict we were able to produce by simply graphing USDA export data [6] and pairing it with global conflict data from the Armed Conflict Location & Event Data Project (ACLED) [7]. Figure 1 displays US exports of corn to Saudi Arabia in 2015 while figure 2 shows actual conflict in Saudi Arabia per month in 2015. Significant spikes in correlation can be seen between both figures 1 and 2 between April and July in each graph.

Within figures 3 and 4, a more striking correlation is very evident. Figures 3 and 4 respectively show US exports of soy to Indonesia and conflict within Indonesia in 2015. Notice the clear alignment of pattern between spikes in each graph from February to May. Our team was very pleasantly surprised with these preliminary findings, especially with the current simplicity of our code and the clear correlation between its outputs.

The input values can be seen below the two sets of figures within tables 1 and 2. Table 1 displays the USDA data which outlines a specific good and the export of that good from country to country. Table 2 is a sample of the Armed Conflict Location & Event Data Project (ACED) data produced. Within it are conflict locations, their description, their severity, and their conflict type.

These significant and similar spike areas lead us to believe that there may be further correlation that could become more evident as more parameters are put into place. With further research, we will test methods of comparing and quantifying this degree of similarity between conflict and product data. The goal is to be able to use Artificial Intelligence and Machine Learning to produce predictions on where conflicts may arise by utilizing historical data that outlines conflict in certain regions as well as types of product whose trade data correlates to said regional conflict data.

Discussion and Conclusion

Though this is all a preliminary study, we believe that this is certainly a route that should be further explored. We want to be sure not to overstep and assume that this seeming correlation is foundation enough to point to consistent and reliable conflict prediction, only that it is certainly a sure step in the right direction.

With further research and training data, hopefully we will be able to discover and follow trends within the global economy that will point to the probability of domestic or international conflict happening all over the world in real time. To be sure the demand will still remain present however far into history this exploration takes us. To quote the United Nations, "early warning is an essential component of prevention, and the United Nations will continue to carefully monitor developments around the world to detect threats to international peace and security" [8].

Now remains the task of weeding out effective economic market pointers. So far, soybean and other soy products prove promising; however, we don't want to close ourselves off from the idea that there may be certain types of products that are better predictors than others depending on the global location of conflicts.

In any case, the discovery continues at the horizon of efficient conflict prediction and global cooperation, preparedness, and growth.

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External References

- [1] Peace Research Institute Oslo (PRIO). "Conflict Prediction." Accessed June 8, 2020. https://www.prio.org/Projects/Project/?x=1401.
- [2] World Resources Institute. "UN Security Council Examines the Connection Between Water Risk and Political Conflict," November 5, 2018.

 https://www.wri.org/blog/2018/11/un-security-council-examines-connection-between-water-risk-and-political-conflict
- [3] Allansson, Marie. "ViEWS Department of Peace and Conflict Research - Uppsala University, Sweden." Uppsala University, Sweden. Accessed June 8, 2020. https://www.pcr.uu.se/research/views/.
- [4] The Alan Turing Institute. "Predicting Conflict a Year in Advance." Accessed June 8, 2020. https://www.turing.ac.uk/research/impact-stories/predicting-conflict-year-advance.
- [5] "What Is Amazon Forecast? Amazon Forecast."
 Accessed June 8, 2020.
 https://docs.aws.amazon.com/forecast/latest/dg/what-is-forecast.html.
- [6] "USDA ERS Soybeans & Oil Crops." Accessed June 8, 2020.

 https://www.ers.usda.gov/topics/crops/soybeans-oil-crops/.
- [7] "Armed Conflict Location & Event Data Project." Accessed July 20, 2020. https://reliefweb.int/organization/acled.
- [8] "Peace and Security," August 30, 2016. https://www.un.org/en/sections/issues-depth/peace-and-security/.